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Modeling and optimization of laser direct structuring process using artificial neural network and response surface methodology

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A B S T R A C T

Laser direct structuring (LDS) is very important step in the MID process and it is a complex process due to different parameters, which influence on this process and its final product. Therefore, it is very important to use a reliable model to predict, analyze and control the performance of the (LDS) process and the quality of the final product. In this work we develop mathematical models by using Artificial Neural Network (ANN) and Response Surface Methodology (RSM) to study this process. The proposed models are used to study the effect of the LDS parameters on the groove dimensions (width and depth), lap dimensions (groove lap width and height) and finally the heat effective zone (interaction width), which are important to determine the line width/space in the MID products and the metallization profile after the metallization step. We also study the relationship between the LDS parameters and the surface roughness which is very important factor for the adhesion strength of MID structures. Moreover these models capable of finding a set of optimum LDS parameters that provide the required micro-channel dimensions with the best or the suitable surface roughness. A set of experimental tests are carried out to validate the developed ANN and the RSM models. It has been found that the predicted values for the proposal ANN and RSM models were closer to the experimental values, and the overall average absolute percentage errors were 4.02 % and 6.52%, respectively. Finally, it has been found that, the developed ANN model could be used to predict the response of the LDS process more accurately than RSM model.

1. Introduction

The MID process has received great attention in production of the electronic circuit board, due to the suitable quality, flexibility and accuracy for this process. Recently, the MID processes are focused on production of the more fine products or the smallest circuit lines and spaces in the circuit board. In fact, fine products depend on the quality of the micro channel or the groove after the LDS step, which depends on the groove dimensions (groove width and depth), groove lap dimensions (lap width and height) and finally the interaction width, which refers to the width of the circuit line, see Fig.1. All the above dimensions as well as the groove profile after the LDS process depend on the LDS parameters such as

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laser power, laser speed and laser frequency (Bassim & Jörg, 2014; Bassim & Jörg, 2015). Another important requirement for the quality and reliability of the MID products is the adhesion strength of the MID structures. The adhesion force between the metallization and the substrate surface can be classified into two types of the chemical and mechanical adhesion and both these two types of adhesion are affected by the surface roughness, on the other hand, the surface roughness depends on the LDS parameters, (Hans, et al., 2005; Kim, et al., 2005). Moreover, it was found that the groove depth or ablation depth is a very important factor for the adhesion force (Horn et al., 1999). It is very important to mention that the LDS step is the key for producing the fine circuit line/space as well as the high quality and reliability for the MID structure. Artificial Neural Network (ANN) as well as the RAM methods have been used in different fields such as engineering, medicine, economic and others fields.

Sofiane et al. (2003) and Abdoul-Fatah et al. (2009) used the ANN model for modeling the atmospheric plasma spraying (APS) process, which is a very important method in the coating process for different materials such as metallic, ceramic, polymer and composite materials. This model has been used to control the APS process and to study the effect of process parameters on the response such as deposited thickness per pass, coating properties and the influences on the in-service properties.

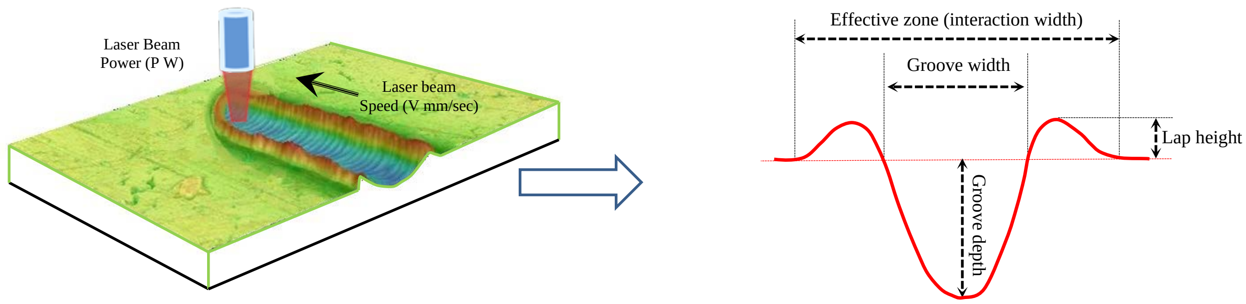


Fig. 1. Laser process and the grove dimensions

Arun and Avanish (2011) used a hybrid approach of Artificial Neural Network (ANN) and Fuzzy Logic (FL), Adaptive Neuron Fuzzy Inference System (ANFIS) as well as the Response Surface Methodology (RSM) for modeling of the laser cutting process for the thin sheet. The researchers used this method for predicting the kerf width (KW) and material removal rate (MRR) and, moreover, to study the effect of the laser parameters including the gas pressure, pulse width, pulse frequency and the cutting speed. The researchers found that the proposed models could be used for the prediction of kerf width and material removal rate in the laser cutting process.

Pragya, et al. (2013) used the RSM and ANN modeling approaches for the wire electric discharge machining (WEDM) of SiCp/6061 Al metal matrix composite (Al MMC) to predict average cutting speed during this process. The researchers used this method to study the effective machining process parameters such as servo voltage (SV), pulse-on time (TON), pulse-off time (TOFF) and wire feed rate (WF), also these models were used to find the most important or effective parameters on the predicted average cutting speed. An ANN approach was developed to predict the CO_2 laser cutting of the stainless steel process by Miloš, et al. (2013). This model was used to study the effect of process parameters such as specific laser energy, focus position and assist gas. The optimum cutting conditions were identified through the ANN proposal model. Miloš, et al. (2015) studied the same laser cutting process with the kerf taper angle obtained in CO2 laser cutting. The researchers used ANN method to propose a model to study the relationship between laser cutting parameters such as laser power, cutting speed, assist gas pressure and focus position, and kerf taper angle also the Monte Carlo method has been widely used to make an optimization for the process parameters.

Mohd et al. (2013) and Kalaiselvan et al. (2014) proposed the ANN in laser micro welding of thin steel sheet to describe the relationship between process parameters and weld bead geometry as well as to predict the weld bead geometry with a wide range of process parameters. The researchers also tested the accuracy of the proposal ANN model by comparing it with actual experimental data for the laser micro welding. The ANN and Multi Regression approaches have been used in another laser application which is the laser Heat-treatment for the 4340 Steel to increase the surface hardness by Ilyes et al. (2014). They proposed a model based on ANN and Multi Regression to predict the hardness profile and depth. These models also have been used to study the effect of process parameters and material properties on the surface hardness as well as to find the most important parameters in this process. The researchers concluded that the ANN and Multi Regression model could be used to simulate this process due to the good agreement with the experimental data.

In the present work, a mathematical model based on ANN and RSM have been developed and implemented for modeling and optimization of LDS process. The proposal mathematical models can be used to simulate the nonlinear and interconnected systems (LDS process) and give an indication about the nonlinear relationship between the most important inputs laser parameters such as laser speed, laser power and laser frequency and the process response (outputs) which are groove dimensions (groove width and depth), lap dimensions (groove lap width and height), the heat effective zone (interaction width) and finally the surface roughness which is very important for the adhesion strength of MID structures. For all the above terms (Outputs) we will find a mathematical model as a function for the laser parameters (Inputs), furthermore the proposal models can be used to find or analyze the effect of each parameters and to suggest the optimum parameters. This will help to achieve the quality and reliability of the MID products moreover to reduce the effort as well as to save significant amount of materials wastage and cost for the requiring experimental tests for the MID process.

2. Experimental Procedure and Details

A set of experimental tests have been carried out in this work to study the effect of the inputs laser parameters on the mean outputs for the LDS process (response). A polymer plates of VESTAMID® HT plus LDS 3031 black, which is a mineral reinforced polyphthalamide (PPA) with glass fiber have been used in this experiments and the dimensions of these plates are 60×60×2 mm, this compound is designed to be used in the production of three dimensional interconnect devices by laser direct structuring, according to the LPKF LDS technology (Technical Information, Evonik Industries, 2014). The laser experiments were performed by a laser machine provided a Nd:YAG laser, the laser machine delivering a laser output power in range of from 1 to 17 W, wavelength of 10.6 μm, and the maximum laser frequency is 200 kHz . Different values of the LDS parameters have been used including the laser powers of 3, 6, 9 and 12 W, laser speeds of 1000, 1300, 1600, 1900 and 2200 mm/s and finally the laser frequencies of 70, 90, 110 and 130 kHz. According to the above process parameters, the total numbers of the experimental tests, which have been carried out in this work are 80. 3D Laser Scanning Microscope (Keyence), have been used to examine the laser effect on the surface of the polymer and measure the effective outputs for the LDS process, including the groove dimensions, lap dimensions, interactive width, and the surface roughness (Ra), see Table 1.

Table 1
The LDS inputs parameters and the experimental measurements for the LDS outputs

Test No.	Laser Parameters			Responses						Test No.	Laser Parameters			Responses					
	P W	V m/s	F kHz	D µm	W µm	L.W µm	L.H µm	I.W.Z µm	Ra µ		P W	V m/s	F kHz	D µm	W µm	L.W µm	L.H µm	I.W.Z µm	Ra µm
1	3	1	70	6.84	33.4	20.9	4.4	75.3	3.	41	9	1	70	25.6	62.7	30.2	7.25	123.2	5.2
2	3	1	90	6.09	30.2	20.4	4.6	71.16	2.	42	9	1	90	18.1	54.5	32.9	8.68	120.3	4.3
3	3	1	11	5.57	27.5	21.4	5.1	70.4	2.	43	9	1	11	19.1	53.4	30.5	11.1	114.4	3.5
4	3	1	13	5	24.7	20.5	5.4	65.85	1.	45	9	1	13	19.0	50.1	30.6	11.0	111.4	3.3
5	3	1.3	70	6.05	30	21.1	4	72.2	3.	44	9	1.3	70	17.6	59.2	18.9	5.63	97	5.3
6	3	1.3	90	4.08	25.3	22.1	4.2	69.52	2.	46	9	1.3	90	17.1	51.8	22.4	6.16	96.7	4.3
7	3	1.3	11	3.61	24.4	20.9	4.3	66.25	2.	47	9	1.3	11	16.9	49.6	22.6	6.8	95	4.2
8	3	1.3	13	3.17	17	21.2	4.3	59.55	2.	48	9	1.3	13	17.6	47.5	22.7	6.75	93	3.9
9	3	1.6	70	4.45	25.5	19.0	2.3	63.55	3.	49	9	1.6	70	14.6	57.5	14.4	3.1	86.4	5.4
10	3	1.6	90	2.46	20	20.7	2.7	61.55	2.	50	9	1.6	90	15.0	49.3	16.4	3.48	82.21	4.8
11	3	1.6	11	2.41	19	20.9	3.3	60.8	2.	51	9	1.6	11	14.5	48	17	4.1	82	4.6
12	3	1.6	13	0	0	27.7	4.5	55.44	1.	52	9	1.6	13	13.4	45.5	17.2	5.4	80	3.9
13	3	1.9	70	3.32	23.2	18.9	2.0	61.11	4.	53	9	1.9	70	11.7	54.3	13.3	2.43	81.05	5.5
14	3	1.9	90	2.3	19	18	1.5	55	2.	54	9	1.9	90	11.7	48.3	14.7	2.6	77.7	4.6
15	3	1.9	11	2.38	18	18	2.9	54	2.	55	9	1.9	11	12.8	47	14	3.82	75	4.7
16	3	1.9	13	0	0	26.6	4.6	53.2	1.	56	9	1.9	13	12.5	44.4	14.8	4.54	74	4.2
17	3	2.2	70	2.9	21.7	18.7	1.6	59.25	4.	57	9	2.2	70	9.93	52.4	10.4	1.6	73.2	5.5
18	3	2.2	90	2.36	18	17.0	1.4	52.1	3.	58	9	2.2	90	9.37	46.4	13.0	2	72.55	4.3
19	3	2.2	11	2.18	17.5	16.1	2.4	49.85	2.	59	9	2.2	11	10.7	45	13.1	2.67	71.3	4.9
20	3	2.2	13	0	0	24.2	4.8	48.5	2.	60	9	2.2	13	10.5	43.6	13.7	3.12	71	4.3
21	6	1	70	17.3	56.3	15.7	5.7	87.8	4.	61	1	1	70	27.4	70.5	35.9	7.5	142.4	5.3
22	6	1	90	16.5	49.4	16.9	5.4	83.4	3.	62	1	1	90	27.1	64.8	35.2	10.8	135.2	4.6
23	6	1	11	16.4	46.2	18.0	7.2	82.35	3.	63	1	1	11	28.7	59.4	37.2	13.8	134	4.8
24	6	1	13	13.1	44	18.6	8.3	81.35	2.	64	1	1	13	28.8	59	37	15.9	133	4
25	6	1.3	70	14.9	54.5	12.3	5	79.2	4.	65	1	1.3	70	18.8	64.6	35.3	6.03	135.2	5.1
26	6	1.3	90	12.8	42.6	17.3	4.7	77.22	4.	66	1	1.3	90	22.0	62.2	29.1	7.6	120.6	5.1
27	6	1.3	11	13.5	41.6	17.2	5.9	76	3.	67	1	1.3	11	24.3	55.6	30.4	9.95	116.5	5.1
28	6	1.3	13	10.9	36.3	19.3	6.1	75	3.	68	1	1.3	13	22.9	54	30.4	11.3	114.8	4.6
29	6	1.6	70	10.9	50	13	2.7	76	4.	69	1	1.6	70	14.6	61.3	31.5	5.2	124.4	5.4
30	6	1.6	90	11.1	40.2	17.3	2.6	74.94	4.	70	1	1.6	90	19.8	55.1	30.5	5.56	116.1	6.2
31	6	1.6	11	11.1	39.5	16.9	3.8	73.5	4.	71	1	1.6	11	19.1	51.9	29.2	6.31	110.3	5.9
32	6	1.6	13	9.4	34.6	18.9	5	72.5	3.	72	1	1.6	13	20.4	51	32.7	8.83	116.4	4.8
33	6	1.9	70	8.8	45.4	12.4	2	70.37	5.	73	1	1.9	70	11.7	57.4	27.4	3.21	112.3	5.9
34	6	1.9	90	7.75	38.1	15.2	2.1	68.65	4.	74	1	1.9	90	15.0	52.2	28.2	4.5	108.6	6.2
35	6	1.9	11	9.8	37.4	15.0	3.2	67.5	4.	75	1	1.9	11	17.1	49.7	27.7	5.67	105.2	6.1
36	6	1.9	13	8.47	34	16.2	3.7	66.5	3.	76	1	1.9	13	16.3	48.4	31.4	6.57	111.3	4.9
37	6	2.2	70	6.87	40	13.7	1.6	67.5	5.	77	1	2.2	70	9.96	54	23.7	2.63	101.4	5.5
38	6	2.2	90	5.71	33.7	16.3	2.1	66.36	4.	78	1	2.2	90	11.5	48.7	23.5	2.75	95.8	5.4
39	6	2.2	11	7.5	31.4	16.0	2.7	63.5	4.	79	1	2.2	11	11.0	46.4	22.4	3	91.33	5.1
40	6	2.2	13	8.03	26	17.6	3.2	61.25	4.	80	1	2.2	13	14.6	44.3	24.3	3.47	93	5.7

3. Mathematical Models

3.1. The RSM Model

Response surface methodology (RSM) is a mixed of mathematical and statistical tools that is powerful to predict and model the response or the outputs for any process which is affected by a number of input variables parameters. The RSM method also can be used to describe the relationship between the response and the input variable moreover to determine the effect of each parameter on the output response. In general the response surface can be expressed as follows, (Andre et al., 2010; Ying, 2011):

$$Y = f\,(\mathrm{P}, \mathrm{V}, \mathrm{F}), \qquad (1)$$

where Y represents the response (output) for the LDS process, P is the laser power (W), V is the laser speed (mm/s) and F is the laser frequency (kHz). Usually a second order polynomial equation can be used to represent response surface for the input factors as follows:

$$\mathrm{Y} = b_0 + \sum_{i=1}^{n} b_i x_i^2 + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i=1}^{n} b_{ij} x_i\, x_j + \varepsilon, \tag{2}$$

where b_0 is a constant of the regression equation, the coefficients, b_i, are linear terms, the coefficients b_{ii}, are quadratic terms and the coefficients b_{ij} are interaction terms. The above second order response model can be expressed as follows:-

$$\mathrm{Y} = b_0 + b_1 P + b_2 V + b_3 F + b_{11} P^2 + b_{22} V^2 + b_{33} F^2 + b_{12} PV + b_{13} PF + b_{23} VF + \varepsilon \tag{3}$$

The Eq. (3) can be used to determine the response equation for the LDS outputs which are the groove depth (G.D), groove width (G.W), lap width (L.W), lap height (L.H), interactive width zone (I.W.Z) and surface roughness (Ra).

3.2. The ANN Model

ANN model has been used to propose a mathematical model in many different fields, which is a computational model inspired by biological nervous systems. The ANN was selected for this work because of its ability to model the non-linear system. In this method, we have a set of procedures as shown in Fig. 2, which shows the mean steps for the ANN methods (Margarita, 2002; Uğur, 2004). In the first step the input and the target or the output data must be defined, in this work, the inputs to the neural networks are the numeric of significant parameters such as laser power, laser speed and finally laser frequency. These inputs influence on the LDS outputs such as groove profile, the groove dimensions, lap dimensions, interactive width and the surface roughness (Ra), see Table 1.

One of the most important and difficult steps in the ANN modeling is the structure or the architecture. Fig.3 shows the neural network architecture employed in this work, this architecture consists of three layers: first layer is the input layer, which represents the input vector, the output from each neuron in the input layer can be represents by $w_{xy}x_i$ where w_{xy} represents the weight associated with the connection between the processing element (inputs factor) x_i, and the processing element j_n. The second layer is the hidden layer which receives the signals from the processing elements layer as well as the bias function, Eq. (4) shows the net input to the each neuron in the hidden layer.

$$I_{ji} = \sum_{i=1}^{3} w_{xy} x_i + x_o, \tag{4}$$

where w_{xy} is the weight from the input layer to hidden layer and x_o is the bias for the input layer. The actual output in the hidden layer is calculated by applying the sigmoid activation function to activate each neuron (Uğur, 2004), see Eq. (5).

$$y_i = f\left(I_{ji}\right) = \frac{1}{1+e^{-(I_{ji})}}, \tag{5}$$

The output layer is the final layer, and it is received in neuron *k* the outputs of the hidden and input layers as well as the bias for the input and hidden layer (b1) and (b2) respectively, see Eq. (6).

$$I_{zi} = \sum_{i=1}^{3} w_{xy} x_i + x_o + \sum_{j=1}^{n} w_{yz} y_j + y_o, \tag{6}$$

where n is the numbers of neurons in the hidden layer and w_{yz} is the weight from the hidden layer to output layer and y_o is the bias for the hidden layer. By applying the same sigmoid function as applied for hidden layer, the actual output in the output layer is calculated by using Eq. (7).

$$z = f(I_{zi}) \tag{7}$$

The training process for the ANN model is the next step to find the sets of weight values that can match the designed network output with the actual target values. Next, the error between desired values and the output value of the network is computed for each output neuron. The other steps for the ANN model can be seen in the Fig.2.

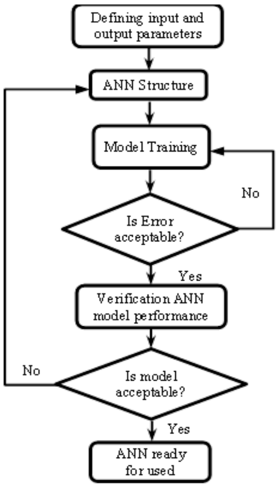


Fig. 2. Steps of ANN modeling

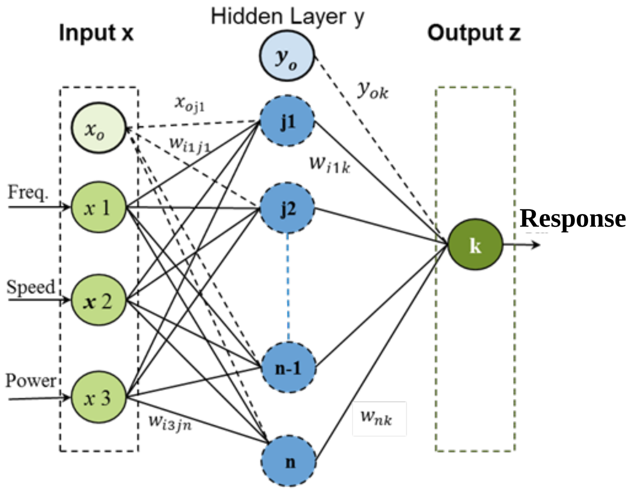


Fig. 3. Architecture for the ANN model

4. Results and Discussion

4.1. The RSM mathematical model.

The mathematical models, which correlate the considered input LDS process parameters and the measured responses such as surface roughness, interactive width, groove depth and width, and lap depth and height, have been developed based on the RSM technique. The final equations for the above responses have been predicated by calculating the coefficients of the polynomial equation for the responses in Eq. (2). These coefficients give an indication about the effect for each LDS parameters on the process response. Table 2 shows the coefficients for all process responses.

Table 2
The coefficients for all process responses

	Ra (μm)	I.W.Z (μm)	G.W (μm)	G.D (μm)	LH (μm)	LW (μm)
Cons(bo)	3.434	130.246	56.11	16.55	8.371	37.06
P(b1)	0.370	3.577	9.089	3.692	0.374	-2.756
V(b2)	0.002	-0.042	-0.024	-0.015	-0.007	-0.009
F (b3)	-0.050	-0.577	-0.405	-0.108	-0.007	-0.086
P^2(b11)	-0.023	0.409	-0.454	-0.101	0.036	0.431
V^2(b22)	-6.5E-7	9.00E-6	3.9E-6	3.10E-6	2.7E-6	2.5E-6
F^2 (b33)	3.4E-5	0.002	0.001	0.000	0.000	0.001
PV(b12)	2.5E-5	-0.002	0.000	-0.001	-0.001	-0.001
PF(b13)	0.002	-0.001	0.013	0.012	0.004	-0.007
VF(b23)	4.6E-6	4.97E-5	-1.58E-5	4.37E-5	-2.3E-5	3.2E-5

Table 2 shows the coefficient for each process parameters referred to the effect of these parameters on the final process response. For example, in the developed model for the interactive width, it can see from this table that the b1>b3>b11>b2>(b33=b12)>b13 so that the laser power is the first and most the effective parameter, the frequency is the second and the laser speed is the third effective parameter. The validity of these models has been checked through 80 confirmation experiments and it is observed that the developed RSM model could predict the responses satisfactorily as average percentage of prediction errors for interactive width and the groove depth are 3.94% and 4.55%, while these errors for the others responses were 6.74%, 7.25%, 7.9% and 8.76 % for the Groove depth, surface roughness, lap width and finally lap height respectively. The overall errors percentage was 6.52%.

4.2. The ANN Mathematical Model.

In the ANN proposal model, 80 experimental tests were used for training the ANN by using MATLAB R2014a and IBM SPSS 22 software. The number of the neurons in the input layer is 3: one hidden layer as well as one neuron at the output layer for calculating the process response. It was found that the numbers of the neurons in the hidden layer were different depending on the process response. The developed ANN model have been used to find the final equations for each process response (by using equations 4 to 7), as well as to find the importance of each process parameters. Table 3 shows the importance of the LDS parameters for each process response as well as the best ANN architecture for the developed models.

Table 3
The importance for the LDS parameters

Parameters	Ra	I.W.Z	G.W	G.D	LH	LW
Power	0.543	0.585	0.573	0.560	0.305	0.553
Speed	0.194	0.330	0.206	0.355	0.471	0.326
Frequency	0.263	0.085	0.221	0.085	0.223	0.120
ANN architecture	3-4-1	3-5-1	3-4-1	3-3-1	3-4-1	3-3-1

From Table 3, we can see that the surface roughness and the groove width were affected by: First, the laser power, second the frequency and then the laser speed, whereas, the interactive width, groove depth and lap width were affected by: First, the laser power, second, the laser speed and finally the frequency. But only the lap height is affected by the laser speed followed by the laser power and frequency. The ANN developed model to predict the process response gives excellent results when compared with experimental tests. Table 4 shows the average percentage errors for the predicted response for the RSM and ANN developed models. From this table it can be concluded that the developed ANN model could predict the process more accurately than RSM developed model, where, the minimum value of the error by the ANN model is 2.29% while it is 3.94% for the RSM. The maximum errors value for the ANN and RSM models are 6.38% and 8.76% respectively

Table 4
The average Errors for the ANN and RSM models

Responses	ANN	RSM
Ra	4.16	7.25
Interactive Width	2.29	3.94
Groove Width	2.86	4.55
Groove Depth	3.88	6.74
Lap Height	6.38	8.76
Lap Width	4.59	7.9
Overall Error	4.02	6.52

Fig. 4 to Fig. 9 show the comparison of results obtained by the ANN and RSM models with the experimental tests. It is observed that the predicted values agree with the measured values for the surface roughness, the interactive width, the groove width, the groove depth, lap height and lap width as well as the errors percentage for these models.

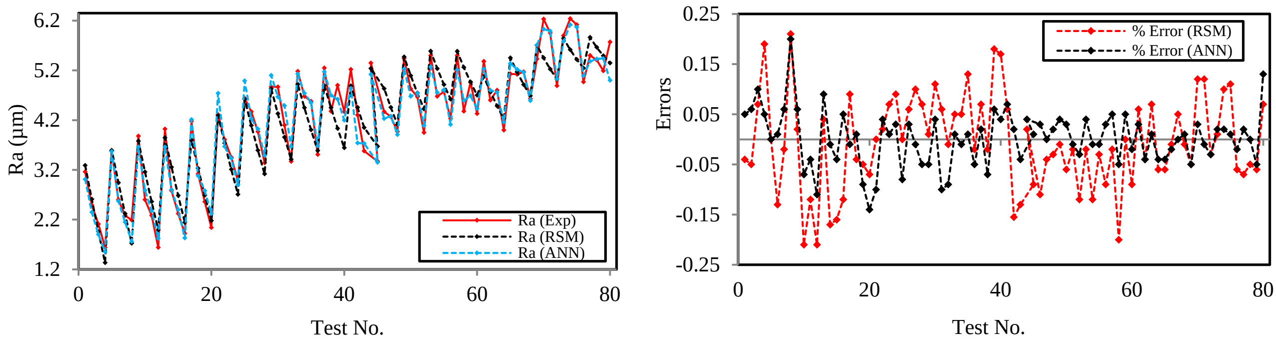


Fig. 4. Ra and % Errors comparison for the ANN and RSM

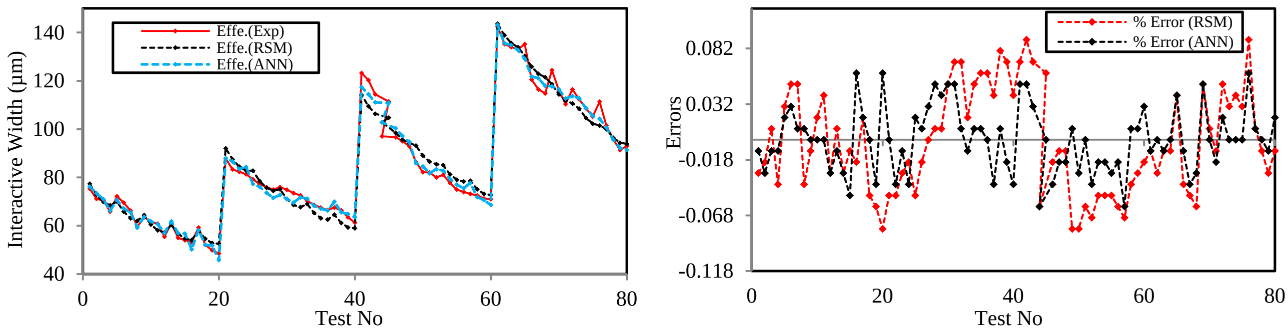


Fig. 5. I.W.Z and % Errors comparison for the ANN and RSM

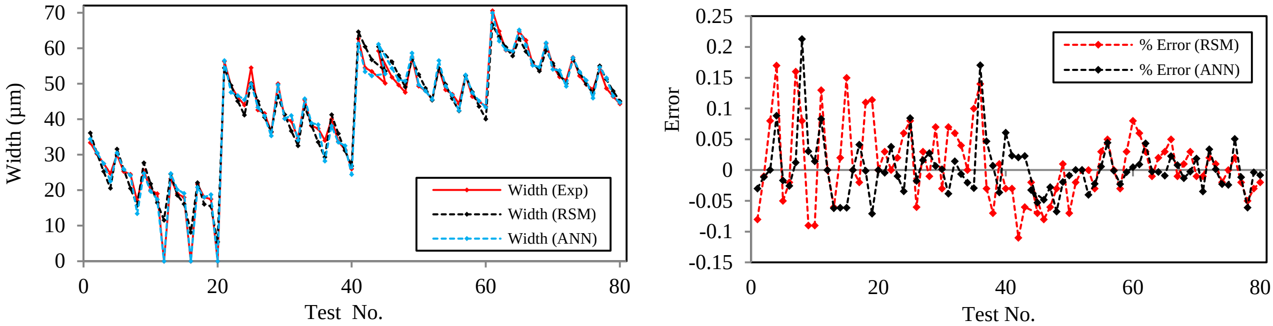


Fig. 6. G. W and % Errors comparison for the ANN and RSM

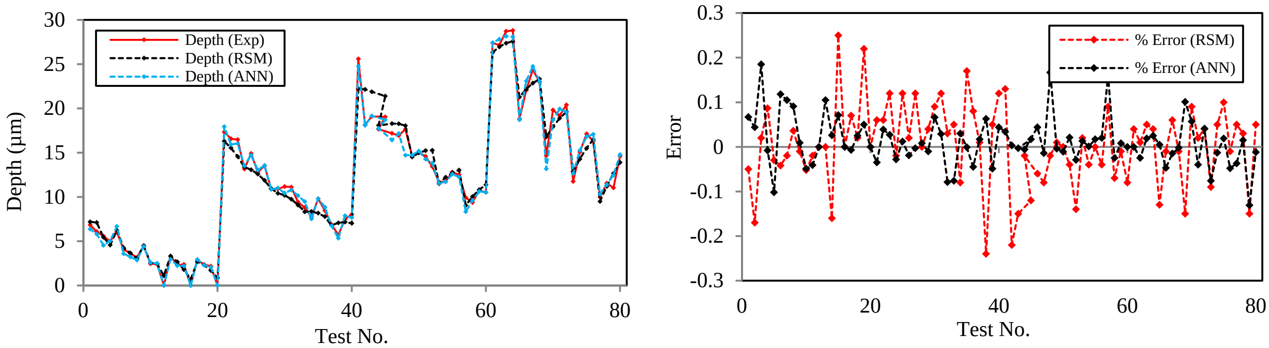


Fig. 7. G. D and % Errors comparison for the ANN and RSM

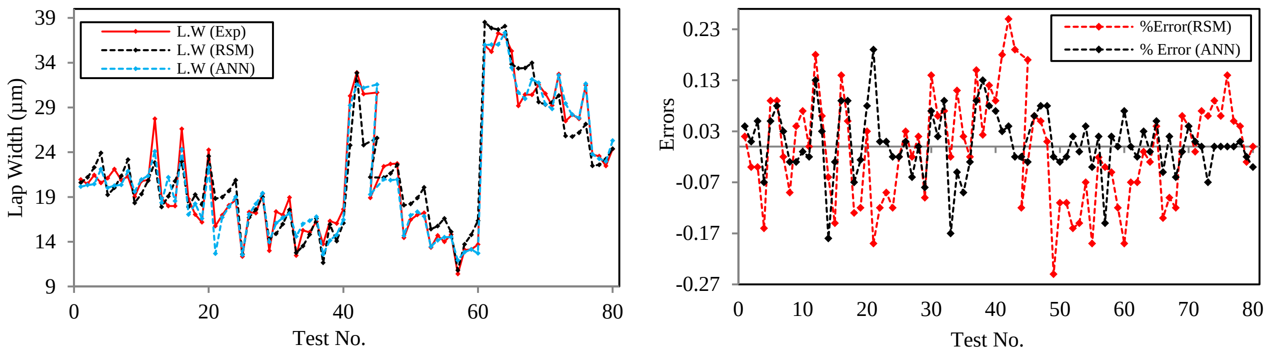


Fig. 8. L. W and % Errors comparison for the ANN and RSM

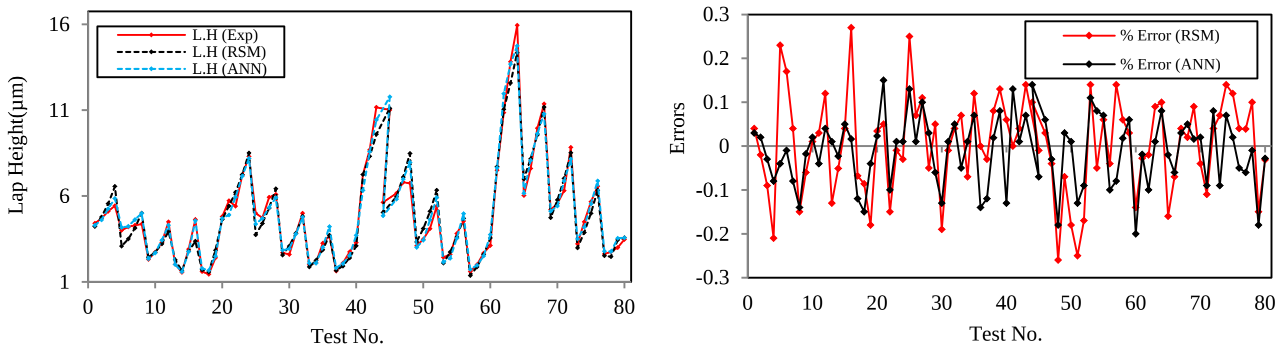


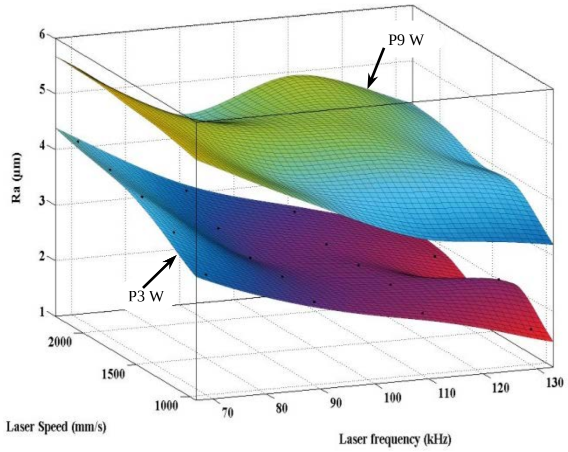
Fig. 9. L. H and % Errors comparison for the ANN and RSM

4.3. The Effects of LDS Parameters on the Process Response

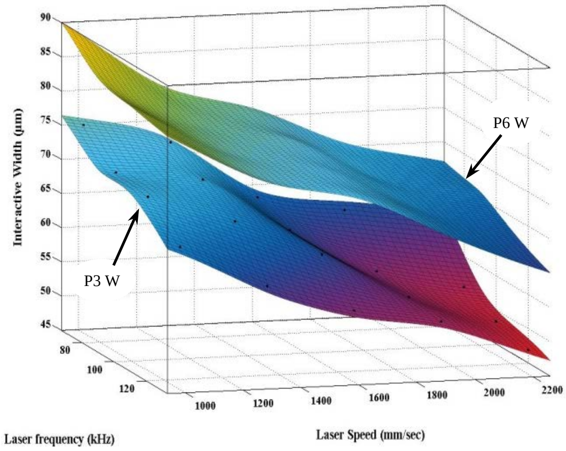
As we mentioned earlier, the quality and the reliability must be achieved for the MID products. The lines/space is very important factor for the quality of the MID products; on the other hand the line width depends on the interactive width, whereas the space between two lines depends on the lap width. The reliability of the MID products depends mainly on the adhesion force. Moreover, there is a very important relationship between the adhesion force and the surface roughness, the groove depth and the laser power (Horn et al. 1999, Hans et al., 2005; Kim et al., 2005). It was found that the adhesion force increase with increasing the Rz (from smooth to rough surface), groove depth and laser power. This is absolutely due to increasing the contact surface between the metallization and the substrate surface, for the rough surfaces. In this section, we will use the ANN mathematical model to analyze the effect of the laser parameters on the process responses which are the interactive width, groove depth, lap width and the surface roughness (Ra) will be investigated, due to the importance of these process responses on the MID products, see Fig.10. It can be seen from this figure that the Ra, interactive width, groove depth and the lap width will be increased when the laser power increases. But when the laser speed increases the interactive width, groove depth and the lap width will be decreased whereas the Ra increases. There is an important effect for the laser frequency on the Ra, but when the frequency increases the Ra will be decreased; also it is very important to note that the effect of frequency on the Ra is more than the effect of the laser speed. The lap width increases when the frequency increases, whereas there is no high effect for the laser frequency on the groove depth and interactive width.

4.4. LDS Process Optimization by ANN Model

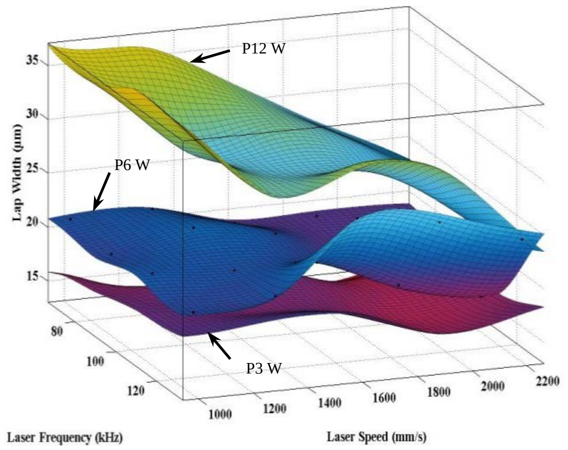
In order to increase the adhesion strength we need to increase the Ra, in other words, the rough surface produces high adhesion force, as mentioned previously, due to increase the contact surface between the two surfaces. In this section we present an attempted to use the ANN developed model to find the optimum LDS parameters by which the quality of MID product (The suitable interactive width, groove depth and lap width), as well as the reliability of the MID products (High adhesion force which depends on the Ra and groove depth). According to the results of the ANN model, the high Ra of 5 µm can achieved by the sets of the laser parameters shown in Table 5.



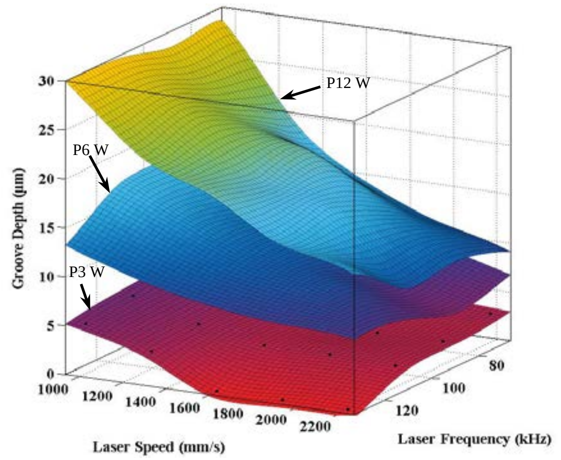
a. Ra at laser power of 3 and 9 (W)



b. Interactive width at laser power of 3 and 6 (W)



c. Lap width at laser power of 3, 6 and 12 (W)



d. Groove Depth at laser power of 3, 6 and 12 (W)

Fig. 10. The effect of the laser power, laser speed and laser frequency on the process responses

This result shows the ANN predicted process response for the interactive width, lap width and groove depth in comparison with additional experimental tests to verify the results of the ANN model. The ANN results are consistent with the experimental data and the minimum percentage errors is 0.03 % while the maximum is 7.4 %. All these parameters give high adhesion force (the requirement for the reliability). But it is very important to find the optimum LDS parameters from these sets which give the best others responses (The suitable interactive width, groove depth and lap width) in order to support the MID quality. Table 5 shows the ANN predicted in comparison with the experimental tests, for the process responses and the corresponding LDS input parameters. From the highest value for the groove depth and because of the adhesion force increase with increasing the groove depth Horn et al. (1999), so that, the optimum LDS parameters are laser power of 12 W, laser speed of 1000 mm/s and laser frequency of 71 kHz, these parameters will be produced an interactive width of 142 µm, lap width of 35,5 µm and groove depth of 27,4 µm. In case of fine line/space products, the interactive width and the lap width must decrease as much as possible. Previously mentioned that the interactive width affects the width of the circuit line, and the lap width affects the space between two circuit lines (Bassim & Jörg, 2015). Consequently the optimum parameters that give minimum interactive width and lap width as well as the highest Ra and groove depth are: First laser power 0f 9 W, laser speed of 1900 mm/s and laser frequency of 79 kHz and the second laser power of 9 W, laser speed of 2200 mm/s and laser frequency of 78 kHz. The first parameters group gives a groove depth of 11,7 µm more than that for the second which is 9,5 µm, so that the adhesion force for the first parameters group better from the second group.

Table 5
Optimum LDS parameters for the Ra 5 (μm)

P (W)	V (m/sec)	F (kHz)	L.W Exp.	L.W ANN	%Err	I.W Exp	I W ANN	%Err	G.D Exp.	G.D ANN	%Err
9	1	73	30.7	30.7	1.2	123	119.5	2.84	24.5	23.8	2.85
12	1	71	35.5	36.8	3.66	142	134.8	5	27.4	27.3	0.03
9	1.3	71	18.9	18.8	0.38	97	101.9	5.13	17.6	17.5	0.27
9	1.6	87	16	16.3	2.37	82.8	80.9	2.24	15.0	15	0.06
12	1.6	71	31	31.5	1.73	124	125.3	1.09	15	13.3	10.8
12	1.6	107	29	30.3	4.75	111	107.9	2.79	19.2	20	4.16
9	1.9	79	14	13	7	79.2	79	0.22	11.7	11.2	4
12	1.9	114.5	27.5	27.9	1.63	106	103.5	2.3	18	17	5.3
9	2.2	78	11.5	12.4	8	72	75.4	4.72	9.5	8.9	5.76
12	2.2	96	23.7	22.8	3.6	94	93.8	0.15	10.9	11.7	7.4
12	2.2	128	24	24.4	1.79	92.8	94.6	1.97	14.2	14.5	2.17
average					3.28			2.58			3.89

5. Conclusions

In this work, ANN and RSM models have used as an alternative for predicating the process response and for analyzing the interdependencies between the process parameters (laser power, laser speed and laser frequency) and process responses and finally to find or estimate the optimum process parameters. The conclusions drawn can be summarized by the following points:

1. The results of the ANN and RSM models were compared with the experimental data show good agreement. The minimum percentage errors for the ANN and RSM models were 2.29% and 3.94% respectively, whereas the maximum value 6.38% and 8.76% respectively, and the overall percentage of prediction errors 4.02 % and 6.52%, for the ANN and RSM models respectively. In general the recorded error was below 12 percent, which falls within acceptable range of modeling standards. It can be concluded that the ANN model can be used efficiently for predicating, analyzing and optimizing more than the RSM model due to its high accuracy.

2. According to the analyzing for the interdependencies between the process parameters and the process responses by using the ANN model, Table 6 shows the concluded relationship. It can be seen from this table that, all the process responses will be increased when the laser power increases, and these responses decrease with laser speed except the Ra which increases with laser speed. Moreover, these responses decrease with laser frequency except the lap dimensions (width and height) will be increased with laser frequency.

Table 6
The effect of parameters on the response

parameters	Response: Ra (μm)	I.W.Z (μm)	G.W (μm)	G.D (μm)	LH (μm)	LW (μm)
Power (W)	0.543 ↑+	0.585 ↑+	0.573 ↑+	0.560 ↑+	0.305 ↑+	0.553 ↑+
Speed (mm/s)	0.194 ↑+	0.330 ↓-	0.206 ↓-	0.355 ↓-	0.471 ↓-	0.326 ↓-
Frequency (kHz)	0.263 ↓-	0.085 ↓-	0.221 ↓-	0.085 ↓-	0.223 ↑+	0.120 ↑+

3. The ANN model has been used to find the optimal LDS parameters to achieve the quality and the reliability for the MID products. It was found that for the reliability it is very important to use a combination of the LDS parameter which leads to maximum Ra and groove depth values; this will help to increase the contact surface and then the adhesion force between the metallization and the substrate surface. Whereas a combination of the LDS parameters lead to minimum interactive width and lap width are suitable for the fine MID products.

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